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Combining data assimilation and machine learning to emulate hidden dynamics and to infer unresolved scale pametrisation.

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A novel method based on the combination of data assimilation and machine learning is introduced. The combined approach is designed for emulating hidden, possibly chaotic, dynamics and/or to devise data-driven parametrisations of unresolved processes in dynamical numerical models.
The method consists in applying iteratively a data assimilation step, here ensemble Kalman filter or smoother, and a neural network. Data assimilation is used to effectively handle sparse and noisy data. The output analysis is spatially complete and is used as a training set by the neural network. The two steps can then be repeated iteratively.
We will show the use of this combined DA-ML approach in two set of experiments. In the first one the goal is to infer a full surrogate model. Here we carry experiments using the chaotic 40-variables Lorenz 96 model and show that the surrogate model achieves high forecast skill up to two Lyapunov times, it has the same spectrum of positive Lyapunov exponents as the original dynamics and the same power spectrum of the more energetic frequencies. In this context we will also illustrate the sensitivity of the method to critical setup parameters: the forecast skill decreases smoothly with increased observational noise but drops abruptly if less than half of the model domain is observed.
In the second set of experiments, the goal is to infer unresolved-scale parametrization. Data assimilation is applied to estimate the full state of the system from a truncated model. The unresolved part of the truncated model is viewed as model errors in the DA system. In a second step, ML is used to emulate the unresolved part, a predictor of model error given the state of the system. Finally, the ML-based parametrisation model is added to the physical core truncated model to produce a hybrid model.
Experiments are carried out using the two-scale Lorenz model and the reduced-order coupled atmosphere-ocean model MAOOAM. The DA component of the proposed approach relies on an ensemble Kalman filter while the ML parametrisation is represented by a neural network. We will show that in both cases the hybrid model yields better forecast skills than the truncated model, and its attractor resembles much more the original system's attractor than the truncated model.

Thematic area

1. Machine Learning for Data Assimilation - Including Model Error Estimation and Correction, Parameter estimation, Fast linearised models for DA, Hybrid DA

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